

# Energy efficient clustering-based routing algorithm for internet of things

Aya Saad, Islam M. Hegazy, El Sayed M. El-Horbaty

Department of Computer Science, Faculty of Computer and Information Sciences, Ain Shams University, Cairo, Egypt

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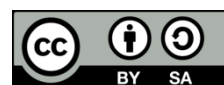
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## ABSTRACT

Routing process is one of the most critical processes in wireless sensor network (WSN). Due to WSN is mainly used in many applications in internet of things (IoT), routing algorithm can affect the performance of these applications. Thus, the usage of inefficient routing algorithm may lead to losing the data collected by sensors. Moreover, it will cause the sensors to waste energy. This paper proposes an energy efficient clustering-based routing algorithm that is based on tunicate swarm algorithm (TSA). TSA-based clustering algorithm selects the optimal cluster head by calculating the remaining energy, the distance to the base station (BS), the distance to each cluster member and balancing the load between the created clusters. TSA-based routing algorithm is used to create paths from cluster heads to the BS using relay nodes. The TSA-based routing algorithm creates the paths based on the path length, the count of relay nodes in the path, and the number of cluster members of each relay node. The result shows that the proposed algorithm is promising in respect of extending the lifetime of the network and conserving the energy.

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## Corresponding Author:

Aya Saad

Department of Computer Sciences, Faculty of Computer and Information Sciences, Ain Shams University  
Cairo, Egypt

Email: aya.saad@cis.asu.edu.eg

## 1. INTRODUCTION

Internet of things (IoT) is a paradigm of wireless telecommunication things. Where different types of things like home appliances, vehicles, and people are attached with sensors, actuators, software, and other technologies to collect data [1], [2]. Things are connected by the internet to transmit the collected data. The IoT application is used in many different fields such as military, medicine, agriculture, transportation, education, smart cities, and other fields [3]. Wireless sensor network (WSN) is one of the most used technologies in IoT applications. Whereas a large number of sensor nodes are located in the environment to sense and transmit important data to the base station (BS) [4]. Where processing and analysis operations are performed on the data to make decisions according to the received data [5]. Sensor nodes are attached with a limited source of energy such as batteries. Due to the sensors may be deployed in remote areas that are difficult to reach, this makes replacing or recharging batteries attached to them difficult [6], [7]. Owing to the process of sending the data to the BS may consume a lot of energy, finding an energy efficient routing algorithm will help rationalize energy consumption. Moreover, it will keep the sensors alive for a longer time.

Many traditional routing algorithms such as greedy perimeter stateless routing (GPSR) [8], low-energy adaptive clustering hierarchy (LEACH) [9], hybrid energy-efficient distributed (HEED) [10], threshold sensitive energy efficient sensor network (TEEN) [11], and other algorithms are used. However,

the traditional algorithms cannot conserve energy which is considered one of the most critical challenges of WSN [12]. Hence researchers are working on proposing efficient routing algorithms that save energy and extend the network lifetime. Recently, researchers started to use bio-inspired algorithms to propose efficient routing algorithms. Whereas bio-inspired algorithms are usually exploited to solve complex optimization problems [13]. Genetic algorithm (GA) [14], particle swarm optimization (PSO) [15], ant colony optimization (ACO) [16], firefly algorithm (FA) [17], grey wolf optimization (GWO) [18], and whale optimization algorithm (WOA) [19] are some of the most frequently used algorithms.

An improved version of LEACH algorithm is introduced. In the new version of LEACH algorithm, the cluster member selects a cluster head if it has the shortest path to the BS [20]. Furthermore, it selects a cluster head if the total distance from the node through the cluster head to the BS is the shortest one. The algorithm outperforms the traditional LEACH algorithm. Despite the proposed algorithm reducing energy consumption compared to the traditional algorithm, the energy factor is not considered while selecting cluster heads. This may negatively affect the sensor node's lifetime.

A cluster-based routing algorithm is proposed in [21]. The algorithm is based on sailfish optimization algorithm (SOA) to choose the optimal cluster heads. Three factors are considered while selecting the cluster heads. The factors are number of neighbors, residual energy, and distance from the node to the BS. The Euclidean distance is calculated to perform cluster formation. Where the normal node joins the cluster of the closest cluster head. The data is transmitted directly to the BS using the cluster head. The algorithm provided a good result in terms of end-to-end delay and network lifetime.

An efficient clustering-based routing algorithm called GA-based clustering and PSO-based routing (GA-PSO) is proposed in [22]. The optimal cluster head is selected using GA. PSO is used for creating the optimal routing paths for every cluster head to the BS to send the data. The objective function of the GA-based clustering algorithm considered the total system energy, the distances to the BS, the distance from the node to its BS, and the distance from cluster members to its cluster head. While the objective function of the PSO-based routing algorithm considered the length of the path and the number of relay nodes in the path. The algorithm is compared to other algorithms. It outperforms the other algorithms regarding energy consumption and network lifetime.

Maheshwari *et al.* [23] proposed butterfly optimization algorithm (BOA), ACO-based clustering, and routing algorithm for WSN. Where BOA is employed to choose the optimal cluster head. Many factors are considered while selecting the best cluster head. These factors are the remaining energy in the cluster heads, the distance from the cluster member and its cluster head, the distance from the cluster head and the BS, node degree, and node centrality. While routing paths from the selected cluster head to the BS are created using ACO. The routing paths are created based on the distance to the BS, node degree of the next hop, and residual energy. The proposed algorithm provided an acceptable performance regarding network lifetime, alive nodes, and conserving energy.

Energy-aware GWO-based routing is proposed for WSN in [24]. To avoid the local optima problem of GWO, the authors proposed a balancing factor between the exploration and exploitation phases of the GWO algorithm to overcome this problem. In the exploration phase, the authors work on changing the linearity of GWO parameters to be non-linear parameters. Moreover, they enhance the exploitation phase by applying a local search around the alpha wolf. If the local search generates a better solution, then the alpha wolf will update its position according to the generated solution. They use the improved grey wolf optimization (IGWO) for choosing the fittest cluster heads. Whereas the objective function of the IGWO-based clustering algorithm depends on the residual energy of the cluster heads and the distance from each cluster member to the cluster head. Furthermore, the IGWO is used to create the routing paths from cluster heads to the BS. Three objectives are considered while creating the paths. The objectives are the energy of the next hop, the distance to the next hop, and the count of the cluster members of the next hop. The algorithm overcame the other algorithms in terms of network lifetime and energy conservation.

Punithavathi *et al.* [25] proposed black widow optimization (BWO) with an improved ACO cluster-based routing algorithm. BWO is used for choosing the best cluster head. The selection of the optimal cluster heads depends on node degree, node centrality, inter-cluster and intra-cluster distance, and residual energy. For creating routing paths for inter-clusters communication, improved ACO is used. Where Krill herd (KH) algorithm is used with traditional ACO to enhance its performance. Energy factor is considered while creating the routes to the BS to identify the minimum and maximum energy path. The algorithm overcame the other algorithms with which it was compared, in respect of residual energy and network lifetime.

An efficient cluster-based routing algorithm using tunicate swarm algorithm (TSA) is proposed in this paper. TSA is a new bio-inspired algorithm. Where it is employed to choose the best cluster heads and to create the routing paths to the BS. Efficient objective functions are formed for choosing the fittest cluster head and creating the optimal paths. Where the objective function of TSA-based clustering depends on

maximizing the residual energy of the picked out cluster heads and minimizing the distances from cluster members to the cluster heads. Furthermore, the objective function depends on minimizing the distances from cluster heads to the BS and balancing the load on the selected cluster heads. While the objective function of TSA-based routing works on minimizing the count of relay nodes in the route, minimizing the length of the transmission distance, and choosing the relay nodes with fewer cluster members to create the path to the BS.

## 2. METHOD

This section describes the network and the energy model. The network structure and assumptions are explained in detail. The theory of the TSA is studied. Moreover, there is a clarification for the mathematical model of the algorithm.

### 2.1. Network model

In our proposed algorithm, it is assumed that the network contains  $N$  sensor nodes. These nodes are initialized in random positions in the network area (see Figure 1). The BS is in the middle of the network. All the sensor nodes have the same initial energy. While the BS has no energy constraints. Each normal node transmits the collected data to its cluster head. The data collected by the cluster head is transmitted to the BS using relay nodes.

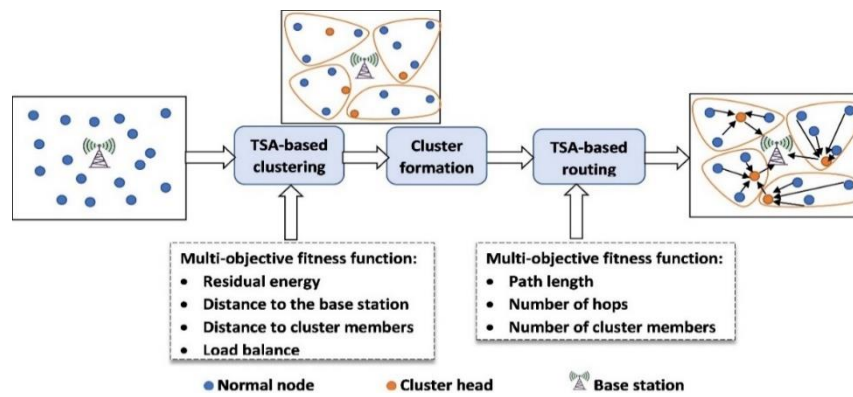


Figure 1. The overall process of the proposed clustering-based routing algorithm

### 2.2. Energy consumption model

The used energy consumption model in our proposed algorithm is the first order radio model [9]. The distance between nodes and the quantity of sent data are affecting the consumed energy by the nodes. The consumed energy to send bits  $E_{TX}$  is calculated as in (1):

$$E_{TX} = \begin{cases} b * E_{elec} + b * E_{fs} * d^2, & \text{if } d < d_0 \\ b * E_{elec} + b * E_{mp} * d^4, & \text{if } d \geq d_0 \end{cases} \quad (1)$$

Where  $b$  is the number of transmitted bits,  $E_{elec}$  is consumed energy per bit while transmitting it,  $E_{fs}$  is the consumed energy per bit to transmit it in free space,  $E_{mp}$  is the consumed energy per bit to transmit it in multipath,  $d$  is the distance that  $b$  bits will be transmitted across, and  $d_0$  is a distance threshold calculated as in (2). While (3) calculates the consumed energy to receive  $b$  bits.

$$d_0 = \sqrt{\frac{E_{fs}}{E_{mp}}} \quad (2)$$

$$E_{RX} = b * E_{elec} \quad (3)$$

### 2.3. Tunicate swarm algorithm

TSA is a bio-inspired algorithm that was recently introduced in [26]. The algorithm mimics the behavior of a marine animal called tunicate. This animal emits green and blue lights that can be seen from long distances [26]. This algorithm was introduced to solve global optimization problems. The mathematical

model of TSA mimics the jet propulsion and the swarm behavior of tunicates while searching for food source [27]. Many factors affect the movement of tunicates to avoid the conflict and balance the swarm force of tunicates. These factors are the gravity and social forces of the swarm. The gravity force  $\vec{G}$  that will affect the movement of the swarm is calculated as in (4). The swarm force  $\vec{F}$  is calculated as in (5). The swarm force will affect the movement of the tunicates.

$$\vec{G} = r_1 + r_2 - 2 \cdot r_3 \quad (4)$$

$$\vec{F} = [V_{min} + r_3 \cdot V_{max} - V_{min}] \quad (5)$$

Where  $r_1$ ,  $r_2$ , and  $r_3$  in (4) are random values in range of [0,1]. As shown in (5), the social interaction between tunicates is affected by primary and secondary speeds  $V_{min}$  and  $V_{max}$ , sequentially. The values of  $V_{min}$  and  $V_{max}$  equal 1 and 4, respectively.

$\vec{T}$  in (6) is used to update the position of tunicates.  $\vec{D}$  in (7) is the distance to the food source. This distance is used to move toward the optimal position.

$$\vec{T} = \frac{\vec{G}}{\vec{F}} \quad (6)$$

$$\vec{D} = \vec{S} - r_4 \cdot \vec{P}(x) \quad (7)$$

Where  $\vec{S}$  is the position of the food source,  $r_4$  is a random value in the range of [0,1], and  $\vec{P}(x)$  is the tunicate position in iteration  $x$ . Then the position is updated to get closer to the food source using (8). The swarm behavior of the tunicate is calculated by (9) to calculate the new position of the tunicate for the next iteration.

$$\vec{P}(\hat{x}) = \begin{cases} \vec{S} + \vec{T} \cdot \vec{D}, & \text{if } r_4 \leq 0.5 \\ \vec{S} - \vec{T} \cdot \vec{D}, & \text{if } r_4 > 0.5 \end{cases} \quad (8)$$

$$\vec{P}(x+1) = \frac{\vec{P}(x) + \vec{P}(\hat{x})}{2 \cdot r_3} \quad (9)$$

Figure 2 shows a flowchart of the main steps of TSA. First, the population of tunicates is initialized. Second, the fitness value is calculated for each tunicate to select the optimal tunicate. Whereas the optimal tunicate is the tunicate which has the optimal fitness value. Third, while the stopping condition is not met, the position of each tunicate is updated, and the fitness values of tunicates are calculated again to select the tunicate that has the best fitness value. At the end, the tunicate that has the optimal fitness value will be considered the optimal solution.

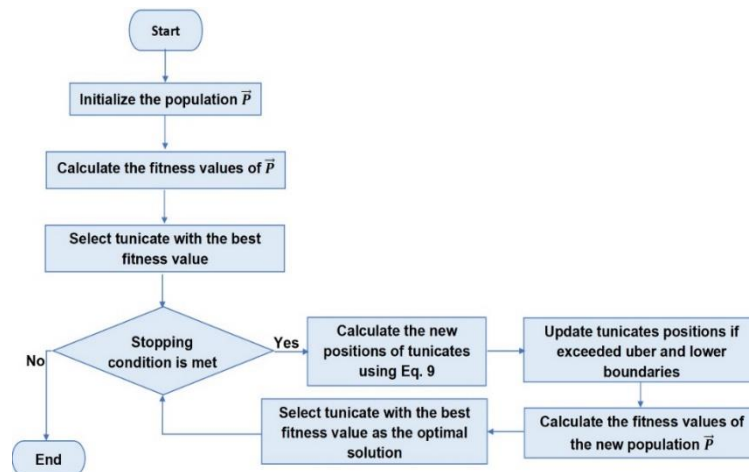


Figure 2. Flowchart of TSA [26]

### 3. THE PROPOSED WORK

In the proposed work, TSA is employed for choosing optimal cluster heads. Moreover, TSA is utilized to construct the optimal path between cluster heads and the BS. In this section, TSA-based clustering

and TSA-based routing algorithms are explained. Furthermore, the objective functions that use in these algorithms are illustrated.

### 3.1. Tunicate swarm algorithm-based clustering algorithm

TSA is adapted to solve clustering problems. In the TSA-based clustering algorithm, each search agent considers a solution that contains the optimal cluster heads. To select the best search agent, the fitness values of search agents are calculated. The one with the optimal fitness value is selected to be the best solution. For calculating the fitness value, four objectives are considered. The first objective is the total remaining energy of the selected cluster heads which is calculated as in (10). The nodes that have the highest energy have a high opportunity to be selected as cluster heads.

$$obj_1 = \sum_{h=1}^H E_h \quad (10)$$

Where  $H$  is the number of cluster heads.  $E_h$  represents the remaining energy of the cluster head  $h$ . The second objective is the distance between the selected cluster head and the BS. The second objective is calculated as in (11). The nodes, which have the shortest distance to the BS, have the highest priority to be cluster heads.

$$obj_2 = \sum_{h=1}^H D(CH_h, BS) \quad (11)$$

Where  $D(CH_h, BS)$  is the Euclidean distance from the cluster head  $CH_h$  to the BS. The distance from the cluster head to its cluster members is the third objective. The third objective is calculated as in (12):

$$obj_3 = \sum_{h=1}^H \sum_{m=1}^M D(CH_h, CM_{h,m}) \quad (12)$$

Where  $D(CH_h, CM_{h,m})$  represents the Euclidean distance from the  $h$ th cluster head  $CH_h$  to its cluster member  $CM_{h,m}$ .  $M$  serves as the count of cluster members in the  $h$ th cluster while  $m$  is the current cluster member in the  $h$ th cluster. The fourth objective is to balance the created clusters using (13):

$$obj_4 = \sum_{h=1}^H abs \left( \frac{N}{H} - Join_h \right) \quad (13)$$

Where  $N$  is the count of normal nodes,  $H$  represents the count of cluster heads, and  $Join_h$  is the count of normal nodes which join the  $h$ th cluster. Due to the objective function being used to find the objective value of each search agent, in (14) is used to determine the fitness of each solution. Our objective is to minimize the fitness value to get the best solution.

$$Fitness = w_1 * \frac{1}{obj_1} + w_2 * obj_2 + w_3 * obj_3 + w_4 * obj_4 \quad (14)$$

Where  $w_1, w_2, w_3$ , and  $w_4$  are weight parameters and the summation of these parameters equals 1. The value of each weight parameter is decided based on the importance of each objective. To create the clusters, each normal node calculates the distance to each cluster head. If the cluster head is closer to it, it joins the cluster.

### 3.2. Tunicate swarm algorithm-based routing algorithm

TSA is used again for choosing the optimal route from each cluster head to the BS using relay nodes. TSA is used here in a different way. Each tunicate in a search agent was given a random value in the range of [0,1]. This value is updated as in (9). The updated value is used to select the next hop of the current cluster head using (15):

$$NextHop_i = PNH_i(ceil(NNH_i * x_i)) \quad (15)$$

Where  $x_i$  is the updated value of the current cluster head.  $NNH_i$  serves as the count of the relay nodes that one of them can be selected to be the next hop, while  $ceil$  is a function that gives the nearest integer up.  $PNH_i$  is a list of potential next hops for the cluster head.

The objective function aims to minimize the value of the fitness to reach an optimal solution. The objective function considers three objectives. The first objective is to minimize the length of the longest path using (16):

$$obj_1 = Max\{\sum_{h=1}^{HopsCount_i-1} D(P_i(h), P_i(h+1)) \forall i, 1 \leq i \leq M\} \quad (16)$$

Where the  $P(h)$  represents the current node in the path of the  $i$ th node and  $P(h + 1)$  is the next hop in the path. While  $HopsCount_i$  is the total count of hops in for  $i$ th node. The second objective is to reduce the maximum count of hops in the paths as shown in (17). The third one is to reduce the maximum count of cluster members of the relay nodes in the path as in (18).

$$obj_2 = \text{Max}\{HopsCounts_i \forall i, 1 \leq i \leq M\} \quad (17)$$

$$obj_3 = \text{Max}\{MemberCounts_i \forall i, 1 \leq i \leq M\} \quad (18)$$

Where  $MemberCounts_i$  represents the count of cluster members of the relay nodes in the path of the  $i$ th cluster head. The objective function used to calculate the fitness of the solution is calculated as in (19):

$$\text{Fitness} = z_1 * obj_1 + z_2 * obj_2 + z_3 * obj_3 \quad (19)$$

Where  $z_1$ ,  $z_2$ , and  $z_3$  are weight parameters that express the importance of each objective. The summation of the parameters equals 1. The values of these parameters show the effect of each objective on the selection of the optimal solution. Figure 3 shows a pseudocode of the proposed algorithm's fundamental steps. The TSA-based clustering and TSA-based routing algorithm are used to select the cluster heads and create paths to the BS, respectively.

We considered that the locations of the nodes and the BS are not changeable. Thus, the TSA-based clustering and TSA-based routing algorithms are applied only if one of the cluster heads loses half of its energy or if one of the cluster heads becomes a dead node. The energy of the node chosen as a cluster head is considered the initial energy of this cluster head. If one of the cluster heads becomes a dead node or the current energy of a cluster head is lower than or equal to half of its initial energy, the TSA-based clustering and TSA-based routing algorithms will be applied again. Other than this, the same cluster heads and paths are used again to send the data to the BS.

```

Set network and energy parameters.
Initialize N sensor nodes in random positions within the network area.
Broadcast a message from BS to all nodes.
Sending location and energy information of each Sensor node to the BS.
Obtaining nodes information by BS.
Execute TSA-based Clustering to select the optimal cluster heads.
Perform cluster formation.
Execute TSA-based routing to create paths from each cluster head to the
base station.
While Stopping condition is not met
    Check if there is a node become a dead node.
    If one of the cluster head loses half of its remaining energy or
    becomes a dead node.
        Execute TSA-based Clustering algorithm.
        Perform cluster formation.
        Execute TSA-based routing.
    End If
    Transmit the data
End While

```

Figure 3. The pseudocode of the proposed algorithm

#### 4. RESULTS AND DISCUSSION

Our proposed algorithm is simulated using MATLAB 2016. The performance of our proposed algorithm is compared with enhanced LEACH (E-LEACH) [20], IGWO [24], and GA-based clustering and ACO-based routing algorithm (GA-PSO) [22]. Those three algorithms were recently proposed. They have given promising results regarding energy conservation and network lifetime. Simulation parameters, comparison metrics, and results are discussed in the is section.

##### 4.1. Simulation parameters

Table 1 contains the simulation parameters of the network. As shown in Table 1, the energy parameters used in the comparison are akin to those in [9]. In addition, the network area size, number of nodes, and packet size are shown in Table 1. The count of clusters created equals 10% of the count of alive nodes. Table 2 illustrates the parameters of the TSA-based clustering algorithm while Table 3 describes the parameters of the TSA-based routing algorithm. As shown in Table 2, the number of iterations in TSA-based clustering is

100. While in Table 3, the number of iterations in the TSA-based routing algorithm is 50 iterations. The reason for decreasing the number of iterations is that the nodes that participated in the routing problem are fewer than the nodes that participated in the clustering problem. Thus, the routing problem is less complex than the clustering problem. For that reason, it is expected that the TSA-based routing algorithm reaches the optimal solution in a few number of iterations. In Tables 2 and 3, weight values are determined according to the importance of each objective factor.

Table 1. Network parameters

Parameter	Value	Parameter	Value
Network area	100×100 m <sup>2</sup>	Initial energy of nodes	0.5 J
Number of nodes	100	$E_{elec}$	50 nJ/bit
BS position	(50,50)	$E_{fs}$	10 pJ/bit/m <sup>2</sup>
Packet size	4000 bits	$E_{mp}$	0.0013 pJ/bit/m <sup>4</sup>
Number of cluster heads	10% of alive nodes	$E_{DA}$	5 nJ/bit

Table 2. TSA-based clustering parameters

Parameter	Value	Parameter	Value
Search agents	30	$w_1$	0.3
Max_Iterations	100	$w_2$	0.25
$P_{min}$	1	$w_3$	0.2
$P_{max}$	4	$w_4$	0.25

Table 3. TSA-based routing parameters

Parameter	Value	Parameter	Value
Search agents	30	$z_1$	0.25
Max_Iterations	50	$z_2$	0.4
$P_{min}$	1	$z_3$	0.35
$P_{max}$	4		

#### 4.2. Metrics of the comparison

Various metrics are used to compare the proposed algorithm's performance with other algorithms. These metrics are the total residual energy, the total alive nodes, the network lifetime, and the stability period. In this subsection, a detailed description of the metrics utilized to measure the performance of the proposed algorithm is given.

##### 4.2.1. The total residual energy

Energy conservation is one of the most important metrics that show the algorithm's effectiveness. This metric shows if the algorithm could conserve the nodes' energy which leads to extending the network lifetime. Therefore, the residual energy is calculated in each round to measure the performance of the proposed algorithm.

##### 4.2.2. The total alive nodes

One of the essential aims of the routing algorithm is to extend the lifetime of each sensor node itself over the network lifetime as much as possible. This will lead to benefiting from it by collecting more data from the environment. Especially, if sensors are embedded in a remote area.

##### 4.2.3. The network lifetime

Network lifetime represents the period of the network operation until 100% of the nodes die. In our paper, this time is measured by the number of rounds. Whereas every round contains two stages the setup phase and the steady state phase. In the setup phase, if one of the cluster heads loses half of its residual energy or one of them becomes a dead node, the TSA-based clustering, and TSA-based routing algorithms are applied to reselect the optimal cluster heads and recreate paths to the BS, respectively. While in the steady state phase, each node transmits the data to its cluster head. Then, the data is aggregated by the cluster head and is sent to the BS using the path created by the TSA-based routing algorithm.

##### 4.2.4. Stability

Stability is the network lifetime until the first node becomes a dead node. This factor is an important factor in showing the ability of the algorithm in the balance usage of the nodes. Moreover, it shows the algorithm's ability to overcome the hot-spot problem [28] that many routing algorithms may face.

#### 4.3. Performance analysis

Figure 4 shows the total residual energy in joules against the number of rounds for each algorithm. The figure shows that the performance of the proposed algorithm is better in terms of energy conservation. It outperforms the E-LEACH, GA-PSO, and IGWO algorithms. While Figure 5 shows the total alive nodes in each round for all the compared algorithms.

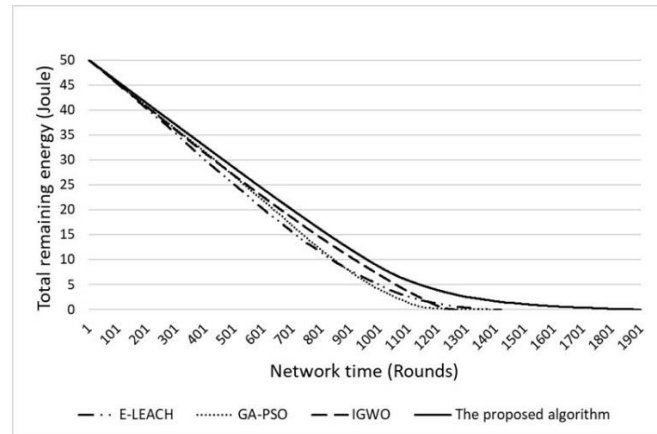


Figure 4. Total residual energy during rounds

As shown in Figure 5 the proposed algorithm keeps nodes alive more than the other algorithms. The proposed algorithm outperforms E-LEACH and GA-PSO in the number of dead nodes during the lifetime of the network. Despite the IGWO overcoming the proposed algorithm in the number of alive nodes from round number 1,010, IGWO drops steeply until all nodes are dead. On the other hand, the count of dead nodes in the proposed algorithm decreases gradually, and in total, it outperforms all the other algorithms. Figure 6 shows stability and network lifetime metrics. The stability period of the proposed algorithm is 504 rounds. While stability periods of E-LEACH, GA-PSO, and IGWO are 317, 319, and 386, respectively.

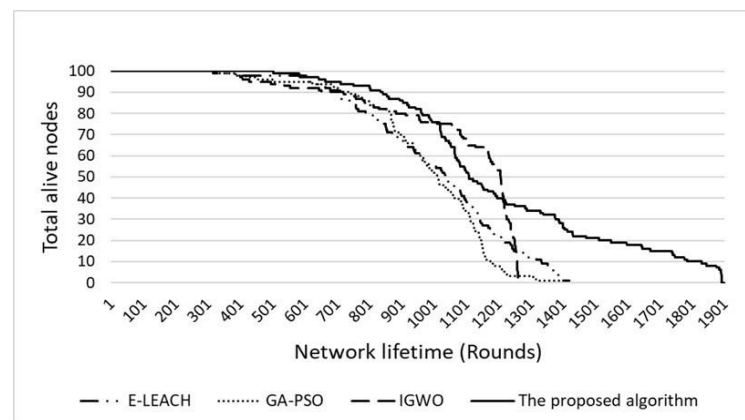


Figure 5. Total alive nodes during rounds

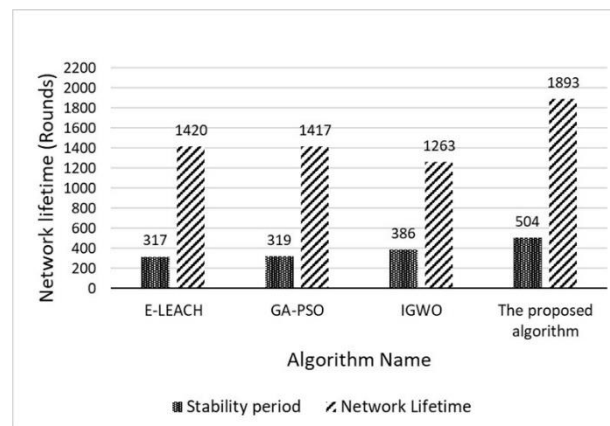


Figure 6. Performance analysis during rounds



This means that the proposed algorithm extends the stability period of E-LEACH, GA-PSO, and IGWO by 37.1%, 36.7%, and 23.4%, respectively. Furthermore, the proposed algorithm performs better than the other algorithms in terms of network lifetime. Where the network lifetime of our proposed algorithm is 1893 rounds. The network lifetimes of IGWO, GA-PSO, and E-LEACH are 1,263; 1,417; and 1,420 rounds, respectively. This means that the proposed algorithm extends the lifetime of the network of IGWO, GA-PSO, and E-LEACH by 33.3%, 25.1%, and 25%, respectively.

## 5. CONCLUSION

An energy efficient clustering-based routing algorithm is proposed in this paper for WSN is proposed. Where TSA is employed for selecting the optimal cluster head and creating the routing paths from every cluster head to the BS. Many factors are considered while selecting the cluster head using TSA-based clustering algorithm. The factors are the remaining energy of cluster heads, the distance from the cluster member to its cluster head, the distance between every cluster head and the BS, and the load on every cluster head. The factors which are considered while creating the routing paths to the BS using TSA-based routing algorithm are the length of the path, the count of hops in the path, and the count of cluster members of each hop in the path. The proposed algorithm is evaluated against E-LEACH, GA-PSO, and IGWO in terms of network lifetime, stability period, number of alive nodes, and total residual energy during rounds. The proposed algorithm outperforms the other algorithms where the proposed algorithm extends the network lifetime 25%, 25.1%, and 33% longer than E-LEACH, GA-PSO, and IGWO, respectively. The proposed algorithm extends the stability period 37.1%, 36.7%, and 23.4% longer than E-LEACH, GA-PSO, and IGWO, respectively. This means that our proposed algorithm can conserve the sensor nodes's energy and keep the nodes alive for a longer time.




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## BIOGRAPHIES OF AUTHORS






**Aya Saad**    received B.Sc. degree in Computer Science from Faculty of Computer and Information Sciences, Ain Shams University, Cairo, Egypt in 2017. Currently, she is a M.Sc. student. She is a teaching assistant in Department of Computer Science, Faculty of Computer and Information Sciences, Ain Shams University Cairo, Egypt. Her research interests focus on IoT, wireless network, and AI. She can be contacted at email: aya.saad@cis.asu.edu.eg.



**Dr. Islam M. Hegazy**    is an Associate Professor in the Department of Computer Science, Faculty of Computer and Information Sciences (FCIS), Ain Shams University (ASU). Dr. Islam has more than 23 years of experience in research and teaching in many fields in Computer Science. He holds a Ph.D. degree from the University of Calgary, AB, Canada. An M.Sc. and B.Sc. degrees, FCIS ASU. His research interests focus on network, security, cloud computing, IoT, image processing, and AI. Dr. Islam acquired several managerial skills as the CIO of ASU, Director of the Scientific Computing Center, FCIS, and the coordinator of the Software Engineering Credit Hours program, FCIS. He can be contacted at email: islhag@cis.asu.edu.eg..



**Professor El Sayed M. El-Horbaty**    received his Ph.D. (1985) in Computer Science from London University, U.K., his M.Sc. (1978) and B.Sc. (1974) in Mathematics from Ain Shams University, Egypt. His work experience as an academic in Egypt (Ain Shams University), Qatar (Qatar University), and Emirates (Emirates University, Ajman University, and ADU University). His current areas of research are distributed and parallel computing, cloud computing, mobile cloud computing, edge computing, e-health computing, IoT, and optimization of computing algorithms. His work appeared in many journals such as: *Parallel Computing*, *International Journal of High Performance and Grid Computing*, *International Journal of Information Security*, *International Journal of Computer Communication and Information Security*, and *International Review on Computers and Software*, *Advances in Intelligent System and Computing*, *International Journal of Mobile Network Design and Innovation*, and *International Journal of Bio-medical Information and e-Health*. He can be contacted at email: shorbaty@cis.asu.edu.eg.